ReaGAN: Node-as-Agent-Reasoning Graph Agentic Network

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Abstract

Graph Neural Networks (GNNs) have achieved remarkable success in graph-based learning by propagating information among neighbor nodes by predefined aggregation mechanisms. However, such fixed schemes often suffer from two key limitations. On the one hand, it cannot handle the imbalance in node informativeness—some nodes are rich in information, while others remain sparse. On the other hand, predefined message passing primarily leverages local structural similarity while ignoring global semantic relationships across the graph, limiting the model's ability to capture distant but relevant information. To address these limitations, we propose Retrieval-augmented Graph Agentic Network (thus named ReaGAN), an agent-based framework that addresses these limitations by empowering each node with autonomous, individual node-level decision-making. Each node is treated as an agent that independently plans its next action based on its internal memory, enabling node-level planning and adaptive message propagation. In addition, retrieval-augmented generation (RAG) is used to enable nodes to retrieve semantically relevant content and build the global relationship among the nodes in the graph. Extensive experiments demonstrate that ReaGAN achieves competitive performance under few-shot in-context settings, using only a frozen LLM backbone without fine-tuning. These results highlight the potential of agentic planning and integrated local-global retrieval for advancing graph machine learning.

1 Introduction

Graph Machine Learning (GML) has achieved remarkable success over the past years, with Graph Neural Networks (GNNs) such as GCN [7], GAT [22], and GraphSAGE [5] becoming the de facto standards for representation learning over graph-structured data. These models operate through a static, globally synchronized message-passing framework, where in each layer, every node aggregates information from its neighbors using a predefined aggregation-update rule parameterized by shared weights across the graph.

While effective in many scenarios, this paradigm suffers from a fundamental limitation: it treats all nodes uniformly, regardless of their varying local context or inherent semantics [3, 14]. The aggregation-update process is entirely homogeneous, where each node follows the same procedure, every layer applies the same function, and no node has the capacity for individualized decision-making. However, graphs often contain a small subset of nodes that are rich in semantic content or structurally well-positioned, while others are sparsely connected, noisy, or contextually ambiguous. Thus, applying identical message-passing rules to all nodes in such settings is problematic: highly
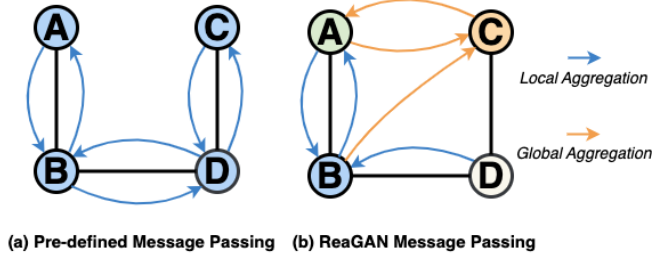
(a) Pre-defined Message Passing   (b) ReaGAN Message Passing

Figure 1: **Message passing in traditional pre-defined way vs. ReaGAN's method.** (a) All nodes only do Local Aggregation. (b) Nodes aggregate in different ways. A's is local and global; B's is local only; C's is global only; D does no operation.

informative nodes may be overwhelmed by irrelevant inputs, while uninformative nodes fail to gather the support they need. Worse still, this homogeneous propagation can amplify noise and redundancy, thereby degrading overall representation quality. This observation motivates ***Challenge 1: Node-Level Autonomy*** — *Can we endow each node with the capacity to autonomously plan its own message-passing behavior based on its internal state and local context, rather than relying on globally shared rules?*

In addition, most existing GNNs operate primarily based on local structural similarity, implicitly assuming that neighboring nodes share informative and task-relevant features. However, this assumption often breaks down in real-world graphs where semantically related nodes may be structurally distant, which is a pattern especially common in open-domain or heterogeneous networks [31, 10]. As a result, traditional GNNs struggle to capture global semantic dependencies, limiting their ability to perform long-range reasoning or generalize beyond local structure. This limitation is especially pronounced in sparsely connected regions, where the local neighborhoods offer limited predictive value [10]. In such settings, retrieving semantically aligned but distant nodes becomes essential for enriching context and improving node representations. This raises ***Challenge 2: Local-Global Complementarity*** — *Can we combine local-structure neighbors with global-semantic neighbors to enable a more comprehensive context-aware message passing?*

To address the two key challenges, we propose a new perspective on graph learning by rethinking the fundamental computational unit: ***we treat each node as an autonomous agent***. Unlike GNNs that passively aggregate messages through static rules, each node acts as an agent who actively determines its action at each layer based on internal states and contextual signals. Inspired by general agent-based systems [17, 23, 24], our agentic framework endows each node with four core components: ***Planning***, which decides the next operations based on its current objective and context; ***Actions***, which executes local-global aggregation strategies to interact with neighbors [25, 18]; ***Memory***, which stores the node's cumulative textual features along with historical interaction traces; and ***Tool Use***, which calls external functions like retrieval-augmented generation. In this work, we unify these components into the **Retrieval-augmented Graph Agentic Network (ReaGAN)**, which enables each node to make individualized, adaptive, and semantically informed decisions. This self-decision design directly addresses Challenge 1 by granting each node autonomy in its message passing, while the local-global aggregation strategy addresses Challenge 2 as the following paragraph shows.

Beyond Local Aggregation which enables nodes to exchange messages with directly connected neighbors, we integrate retrieval-augmented generation (RAG) [9] as an external tool that empowers nodes to access semantically relevant but structurally distant information, where the entire graph is viewed as a searchable database. Each node then integrates both local structural signals and globally retrieved semantic content into its individual memory, forming a richer contextual representation for subsequent planning and interaction. Equipped with these capabilities, each node engages in an agentic workflow. Based on its current state and memory, the node prompts a frozen LLM to generate a context-aware plan, selects and executes the appropriate actions, such as local or global aggregation, optionally invokes external tools like RAG, and subsequently updates its internal memory with the acquired information.

We pinpoint the key differences between traditional message passing and our agentic workflow. As shown in Figure 1(a), standard GNNs enforce a uniform propagation rule, where all nodes solely communicate only with immediate neighbors. In contrast, Figure 1(b) illustrates ReaGAN's

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mechanism, in which each node autonomously selects its own actions and possibly reach its remote yet semantical neighbors. For example, node A performs both local and global aggregation; node B conducts only local aggregation, resembling classical GNN behavior; node C executes only global aggregation; and node D chooses to remain inactive. This demonstrates how ReaGAN supports diverse and asynchronous strategies at the node level, offering a level of node-level flexibility.

We summarize our main contributions as follows:

• We introduce ReaGAN, an agentic graph learning framework that models each node as an autonomous agent equipped with planning, memory, action, and tool-use capabilities, moving beyond static, rule-based message passing in traditional GNNs.

• We introduce a hybrid aggregation mechanism that integrates local structural and global semantic information via retrieval-augmented generation, allowing nodes to dynamically access semantically relevant but structurally distant context.

• We conduct extensive experiments to demonstrate that ReaGAN achieves strong performance over existing traditional methods, even using a frozen LLM without fine-tuning.

2 Method

Node As Agent   In ReaGAN, each node is treated as an autonomous agent capable of perceiving its own state and neighborhood context, planning its next steps, executing context-aware actions, utilizing external tools, and updating its internal memory. This perspective departs from traditional synchronized message passing, instead enabling fully individualized, asynchronous, and adaptive behavior. Moreover, each node can not only aggregate information from local structural neighbors, but also retrieve semantically relevant signals from distant nodes across the graph. By doing so, ReaGAN naturally supports both *node-level personalization and autonomy* (addressing *Challenge 1*) and *joint local-global information integration* (addressing *Challenge 2*).

Agentic Formulation   Let $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ be an attributed graph, where each node $v \in \mathcal{V}$ is associated with a text feature t_v and an optional label $y_v \in \mathcal{Y}$. The goal is to predict labels $\hat{y}_v$ for all unlabeled nodes. Each node is treated as an agent equipped with memory $\mathcal{M}_v$, interacting with a frozen large language model (LLM) through a multi-layered reasoning loop. At each layer, the node constructs a prompt based on its memory, queries the LLM for an action plan, and updates its memory accordingly. After L layers, the node predicts a label by querying the LLM with a prompt derived from its final memory state.

In summary, each node follows a layer-wise cycle of *perception*, *planning*, *action execution*, and *memory update*, independently deciding whether to gather local/global information, make a prediction, or take no action. This fully agentic workflow is detailed in Algorithm 1.

2.1   Planning: Prompting Frozen LLM

In ReaGAN, each node is equipped with a local planner that determines how to act at each layer. Rather than relying on a globally shared aggregation rule, we leverage a frozen large language model (LLM) to enable in-context planning, where decisions are conditioned on the node's own memory. At each layer l, node v constructs a structured prompt based on its internal memory $\mathcal{M}_v^{(l)}$. The prompt is then sent to a frozen LLM (e.g., LLaMA [21], Qwen [28], or DeepSeek [20]), which returns an action plan:

$$a_v^{(l)} = \texttt{LLM}(\texttt{Prompt}_{\texttt{planning}}(\mathcal{M}_v^{(l)}))$$

while the action(s) in $a_v^{(l)}$ are selected from a discrete space and described in detail in Section 2.2. The node then parses and executes the plan, updating its memory with newly acquired information. This process is repeated for L layers. At the final layer, the node constructs a prediction-specific prompt and queries the LLM to produce a label:

$$\hat{y}_v = \texttt{LLM}(\texttt{Prompt}_{\texttt{predict}}(\mathcal{M}_v^{(L)}))$$

which ends up the overall planning loop illustrated in Figure 2. To sum up, the planning process allows each node to reason independently and asynchronously, determining what to do and when

Algorithm 1 Layer-wise reasoning loop for agent node v in ReaGAN

Require: Text-attributed graph $\mathcal{G}$, node v, frozen LLM, retrieval database $\mathcal{D}$
1: Initialize memory: $\mathcal{M}_v^{(0)} \leftarrow \{t_v\}$
2: Initialize aggregated feature: $\tilde{t}_v^{(0)} \leftarrow t_v$
3: **for** layer $l = 1$ to L **do**
4:     $p_v^{(l)} \leftarrow \text{Prompt}_{\text{planning}}(\mathcal{M}_v^{(l-1)})$
5:     $a_v^{(l)} \leftarrow \text{LLM}(p_v^{(l)})$
6:     **for** action a in $a_v^{(l)}$ **do**
7:       **if** $a = \text{LocalAggregation}$ **then**
8:         $\tilde{t}_v^{(l)} \leftarrow \text{TextAgg}(\tilde{t}_v^{(l-1)}, \{\tilde{t}_u^{(l-1)} \mid u \in \mathcal{N}_{\text{local}}(v)\})$
9:         $\mathcal{E}_v^{(l)} \leftarrow \{(\tilde{t}_u^{(l-1)}, y_u) \mid u \in \mathcal{N}_{\text{local}}(v), y_u \in \mathcal{Y}\}$
10:         $\mathcal{M}_v^{(l)} \leftarrow \mathcal{M}_v^{(l-1)} \cup \{\tilde{t}_v^{(l)}\} \cup \mathcal{E}_v^{(l)}$
11:       **else if** $a = \text{GlobalAggregation}$ **then**
12:         $\mathcal{N}_{\text{global}}(v) \leftarrow \text{RAG}(\tilde{t}_v^{(l-1)}, \text{top} = K)$
13:         $\tilde{t}_v^{(l)} \leftarrow \text{TextAgg}(\tilde{t}_v^{(l-1)}, \{\tilde{t}_u^{(l-1)} \mid u \in \mathcal{N}_{\text{global}}(v)\})$
14:         $\mathcal{E}_v^{(l)} \leftarrow \{(\tilde{t}_u^{(l-1)}, y_u) \mid u \in \mathcal{N}_{\text{global}}(v), y_u \in \mathcal{Y}\}$
15:         $\mathcal{M}_v^{(l)} \leftarrow \mathcal{M}_v^{(l-1)} \cup \{\tilde{t}_v^{(l)}\} \cup \mathcal{E}_v^{(l)}$
16:       **else if** $a = \text{Prediction}$ **then**
17:         $p_v^{\text{pred}} \leftarrow \text{Prompt}_{\text{predict}}(\mathcal{M}_v^{(l-1)})$
18:         $\hat{y}_v \leftarrow \text{LLM}(p_v^{\text{pred}})$
19:       **else if** $a = \text{NoOp}$ **then**
20:         $\mathcal{M}_v^{(l)} \leftarrow \mathcal{M}_v^{(l-1)}$ {No change to memory}
21:       **end if**
22:     **end for**
23: **end for**
24: **return** Predicted label $\hat{y}_v$ (if generated)

to act—without any global synchronization. It forms the core mechanism that enables *Challenge 1 (Node-Level Autonomy)* and *Challenge 2 (Global Semantic Access)* to be addressed in a unified and decentralized manner.

2.2 Action: Node-Level Decision Space

The purpose of operating actions is to aggregate information, both from local and global way. The process of aggregation containing enhancing the text feature and collecting neighbor shots. The details will be discussed in the following sections.

2.2.1 Local Aggregation.

We refer to directly connected nodes in the input graph as *local structural neighbors*, and to semantically similar but unconnected nodes retrieved via RAG as *global semantic neighbors*. When a node selects the Local Aggregation action, it gathers information from its local structural neighbors (e.g., 1-hop or 2-hop nodes). This action serves two primary purposes:

- **Feature Enhancement.** All neighbors, regardless of label availability, contribute to a contextual text aggregation process. The node summarizes the textual content of its local neighborhood—typically by generating a single aggregated text snippet $\tilde{t}_v^{(l)}$ that combines its own feature t_v with those of its structural neighbors. This mirrors the feature aggregation in GNNs, where embeddings are iteratively enriched from local neighbors. The aggregated feature is defined as:

$$\tilde{t}_v^{(l)} = \text{TextAgg}\left(\tilde{t}_v^{(l-1)}, \left\{\tilde{t}_u^{(l-1)} \,\middle|\, u \in \mathcal{N}_{\text{local}}(v)\right\}\right)$$

where $\text{TextAgg}(\cdot)$ denotes a natural language-level aggregation function such as concatenation or summarization. Here, $\tilde{t}_v^{(l-1)}$ is the node's aggregated feature from the previous layer (initialized
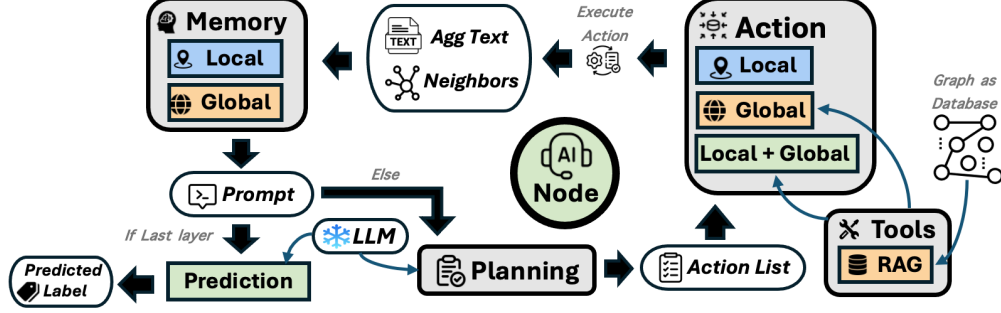
Figure 2: **Overview of ReaGAN.** Each node in ReaGAN is modeled as an agent equipped with four core modules: *Memory*, *Planning*, *Tools*, and *Action*. The node stores its original information and receives local and global information into its memory, constructs a natural language prompt, and queries a frozen LLM for an action plan. The returned plan may contain one or more actions (e.g., Local Aggregation, Global Aggregation), which are executed using available tools such as RAG. The resulting outputs are written back into memory and may produce a predicted label. This forms a closed loop of perception, planning, action, and memory refinement across layers.

as t_v). The result $\tilde{t}_v^{(l)}$ is stored in memory as an updated representation of the node's semantic environment.

- **Few-Shot Example Collection.** From among the labeled structural neighbors, a small subset is selected as in-context examples. Each selected node contributes a (text, label) pair, which is explicitly written into the current node's memory. This supports few-shot label prediction by providing semantically relevant examples during prompt construction:

$$\mathcal{E}_v^{(l)} = \left\{ \left(\tilde{t}_u^{(l-1)}, y_u\right) \,\middle|\, u \in \mathcal{N}_{\text{local}}(v) \wedge y_u \in \mathcal{Y} \right\}$$

Thus, Local Aggregation provides both *semantic enhancement* and *label grounding* through neighboring information. All aggregated summaries and selected examples are written into the node's memory buffer for use in future planning or prediction. The memory update is:

$$\mathcal{M}_v^{(l)} \leftarrow \mathcal{M}_v^{(l-1)} \cup \{\tilde{t}_v^{(l)}\} \cup \mathcal{E}_v^{(l)}$$

2.2.2 Global Aggregation.

The Global Aggregation action enables a node to augment its semantic context by retrieving structurally distant but semantically similar nodes from across the graph. This is achieved by invoking a retrieval tool (e.g., RAG), which queries a structure-free database constructed from all node-level textual representations. Unlike the original graph, this database preserves no edges; each entry consists of a node's text feature t_u and its label y_u (if available). Retrieval is based purely on textual semantic similarity, typically computed via dense embedding similarity (e.g., cosine distance). Given a query node's current textual state $t_v^{(l-1)}$, the system retrieves the Top-K most relevant global semantic neighbors:

$$\mathcal{N}_{\text{global}}(v) = \text{RAG}(t_v^{(l-1)}, top = K)$$

Similar to Local Aggregation, Global Aggregation also serves two main purposes:

- **Feature Enhancement.** The textual features of the retrieved nodes are aggregated to form an updated summary $\tilde{t}_v^{(l)}$ that reflects global semantics, which is appended to the node's memory to enhance its contextual understanding beyond structural proximity:

$$\tilde{t}_v^{(l)} = \text{TextAgg}\left(\tilde{t}_v^{(l-1)}, \left\{\tilde{t}_u^{(l-1)} \,\middle|\, u \in \mathcal{N}_{\text{global}}(v)\right\}\right)$$

- **Few-Shot Example Collection.** From the retrieved nodes with known labels, a subset is selected as few-shot examples for prompt construction:

$$\mathcal{E}_v^{(l)} = \left\{\left(\tilde{t}_u^{(l-1)}, y_u\right) \,\middle|\, u \in \mathcal{N}_{\text{global}}(v) \wedge y_u \in \mathcal{Y}\right\}$$

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Both the aggregated summary and the selected labeled examples are written into the node's memory, which is same as the local version. Through this process, Global Aggregation provides semantic enrichment and label grounding from structure-agnostic sources. It expands each node's informational horizon beyond its local neighborhood—especially benefiting nodes in sparse or isolated regions. This mechanism directly addresses *Challenge 2 (Global Semantic Access)*.

2.2.3 NoOp.

While seemingly trivial, the **NoOp** (no operation) action plays a critical role in regulating information flow. When selected, the node intentionally chooses to take no action in the current layer—effectively pausing further aggregation or decision-making.

This mechanism is essential for avoiding information over-collection, especially in cases where the memory already contains sufficient context. It helps prevents noise accumulation and supports pacing in multi-layer reasoning. By allowing nodes to wait or opt out of message passing altogether, NoOp reinforces ReaGAN's core principle of self-decision and resource-aware adaptation (*Challenge 1*).

2.3 Memory: Tracking the Internal State

As mentioned above, each node maintains a private memory buffer $\mathcal{M}_v$ that accumulates information over time to support reasoning and prediction. This memory includes two types of content from two sources:

- **Local information**: messages and labeled examples from Local Aggregation.
- **Global information**: semantically similar content retrieved via Global Aggregation.

As illustrated in Figure 3, memory entries can also be categorized along a second semantic dimension: in addition to the *source type* (local vs. global), we also consider the *information purpose*. These correspond to the following categories:

- **Text Feature.** The node's raw natural language input t_v, preserved across all layers to serve as an identity anchor.
- **Aggregated Representations.** Natural language summaries collected via Local Aggregation and Global Aggregation. These capture multi-scale contextual signals to enrich node understanding.
- **Selected Labeled Neighbors.** A curated set of (`text, label`) examples drawn from both local and global sources. These are explicitly stored for use in few-shot prediction, injected into the prompt to support semantic reasoning.

Memory is updated incrementally at each layer by adding newly generated entries from the current step:
$$\mathcal{M}_v^{(l)} \leftarrow \mathcal{M}_v^{(l-1)} \cup \{m_i^{(l)}\}_{i=1}^k$$
where $\{m_i^{(l)}\}$ are the new entries produced by actions such as Local Aggregation, Global Aggregation, or retrieval-based example selection at layer l, which is equals to $\tilde{t}_v^{(l)} \cup \mathcal{E}_v^{(l)}$).

As the core source of contextual information, the memory buffer provides the essential components for prompt construction: the original text, aggregated text, and a subset of labeled examples. This allows the prompt to accurately reflect the node's internal state and accumulated knowledge. As each node independently controls its memory and its content evolves through executed actions, this design supports self-individualized behavior (*Challenge 1*). Moreover, by storing semantically retrieved examples from distant nodes, memory also supports context enrichment beyond local structure (*Challenge 2*).

2.4 Tools: Global Semantic Augmentation

To support global semantic reasoning, ReaGAN equips each node with a single external tool: Retrieval-Augmented Generation (RAG). This tool enables a node to retrieve semantically relevant information from across the entire graph—beyond its structural neighborhood. A structure-free database is constructed, consisting of all nodes' text features and, when available, their labels. Each node
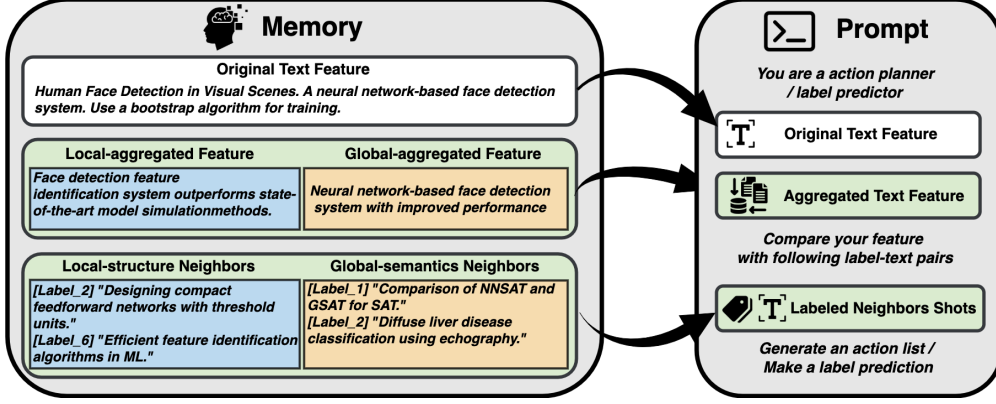
Figure 3: **Information flow from memory to prompt.** Each node's memory includes its original text feature, aggregated text feature from local and global neighbors, and selected labeled neighbor shots. During planning or prediction, these components are selectively injected into a natural language prompt, providing the LLM with (i) the input node's raw identity, (ii) context-enhanced descriptions, and (iii) label-text pairs for few-shot learning. This design enables each agent to reason over multi-scale context and take personalized actions.

contributes a single entry, and the resulting corpus $\mathcal{D}$ is indexed by textual similarity. Given a node's current representation $t_v^{(l)}$, the RAG tool performs a top-K similarity search over the database:

$$\text{RAG}(t_v^{(l)}, top = K) = \text{TopK}\left(\{t_u \mid u \in \mathcal{V}\}, \text{sim}(t_v^{(l)}, t_u)\right)$$

where $\text{sim}(\cdot, \cdot)$ denotes an embedding-based similarity function (e.g., cosine distance).

In this design, RAG functions as a modular tool that enables semantic retrieval for the `Global Aggregation` action. This separation ensures that memory evolution remains fully governed by agent actions, without implicit tool-side updates. By invoking RAG on demand, each node can enrich its local structural context with globally relevant, semantically aligned information—particularly beneficial for nodes situated in sparse or disconnected regions. As such, RAG plays a central role in addressing *Challenge 2 (Global Semantic Access)*.

Overall Execution Flow   ReaGAN transforms each node into an autonomous agent equipped with memory, planning, and external tools. At each layer, nodes operate independently based on their internal state—without global synchronization or shared parameters.

Each reasoning layer follows the following cycle:

- **Perception:** The node gathers contextual signals from its memory and optionally from local neighbors.
- **Planning:** It constructs a prompt and queries the frozen LLM to decide the next action(s).
- **Action:** The selected actions are executed—aggregating information, retrieving global content, or making a prediction—and the outcomes are written into memory.

This process repeats for L layers (typically 1–3), after which each node outputs a predicted label. Through this decentralized execution mechanism, ReaGAN fulfills two key objectives: (1) enabling **node-level autonomy and personalized decision-making** (*Challenge 1*); and (2) integrating **local structural and global semantic information** within a unified agentic framework (*Challenge 2*).

3   Experiments

Based on the challenges identified in Section 1, we formulate the following research questions(RQs):

- **RQ1**: How does ReaGAN perform on node classification tasks compared to standard GNNs?
- **RQ2**: How do the agentic planning mechanism and Global Aggregation contribute to performance?

Table 1: Test accuracy (%) on the Cora, Citeseer, and Chameleon datasets. Traditional GNNs rely on parametric training and fixed message passing, while **ReaGAN** leverages a frozen LLM for agentic planning and personalized reasoning.

Model	Cora	Citeseer	Chameleon
Parametric Training (Supervised GNNs)			
GCN [7]	84.71	72.56	28.18
GAT [22]	76.70	67.20	42.93
GraphSAGE [5]	84.35	78.24	62.15
GPRGNN [2]	79.51	67.63	67.48
APPNP [8]	79.41	68.59	51.91
MLP-2 [29]	76.44	76.25	46.72
MixHop [1]	65.65	49.52	36.28
Frozen LLM + Few-shot Setting			
ReaGAN (Ours)	84.95 ± 0.35	60.25 ± 0.36	43.80 ± 0.65

- **RQ3**: When do agentic nodes need global semantic retrieval to do global aggregation, and how should local and global shots be balanced in prompts?

- **RQ4**: Does exposing label semantics improve classification accuracy in ReaGAN?

Datasets   We evaluate the proposed ReaGAN on the standard node classification task using the **Cora** ,**Citeseer** and **Chameleon** dataset. Each node corresponds to a scientific publication with a textual description, and the goal is to predict its research category. We adopt a 60%/20%/20% split for training, validation, and testing, respectively.

Baselines.   We compare ReaGAN with a set of widely used baselines, including GCN [7], GAT [22], GraphSAGE [5], APPNP [8], GPRGNN [2], MixHop [1], and MLP-2. All models are implemented using PyTorch Geometric with standard hyperparameters and are trained on the same data splits as ReaGAN.

Reproduction Settings.   We conduct all experiments in PyTorch using a cluster of NVIDIA RTX A6000 GPUs. The agentic node reasoning module relies on a frozen LLM, served via vLLM, using Qwen2-14B. We do not perform any fine-tuning. We report test accuracy for node classification. To ensure fair comparison, all baselines are trained under identical splits. We use all-MiniLM-L6-v2 to transfer text to embedding. More experimental details are provided in *Appendix*.

3.1 Overall Performance on Node Classification

To answer **RQ1**, we report node classification accuracy for all baselines and for ReaGAN in Table 1. Despite using no trainable parameters, ReaGAN achieves competitive performance compared to fully supervised GNNs, while enabling node-level autonomy and reasoning via a frozen LLM.

3.2 Impact of Agentic Planning and Global Retrievals

To answer **RQ2**, we perform ablations on ReaGAN's two core components: node-level planning and global retrieval. Removing prompt planning forces all nodes to follow a fixed action sequence, leading to notable accuracy drops due to the lack of context-specific behavior. Disabling global retrieval (Local Only) limits each node to structural neighbors, which underperforms in sparse graphs. Conversely, the Global Only variant removes structural input and struggles in well-connected graphs, showing the need for both structural and semantic signals. Experimental results are shown on Table 2 which shows that both *agentic planning* and *global semantic access* are essential. Removing either component leads to measurable accuracy degradation, validating the effectiveness of our solution to the autonomy and semantic challenges.

To address **RQ3**, we investigate how the balance between local and global memory in the prompt affects node classification accuracy. We perform an ablation study comparing two prompt construction

Table 2: Ablation study on Cora, Citeseer, and Chameleon (Test Accuracy %). ReaGAN's performance depends on both agentic planning and local-global integration.

Model Variant	Cora	Citeseer	Chameleon
ReaGAN (Full)	**84.95**	**60.25**	**43.80**
No Prompt Planning	79.83	35.87	38.29
Local Only	81.67	58.73	25.60
Global Only	79.67	33.45	24.94

Table 3: **Prompt Memory Strategy vs. Accuracy.** Comparison of two prompt construction strategies across three datasets. Strategy A includes both local and global memory in the prompt. Strategy B includes global memory only when fewer than two local entries are available.

Dataset	Strategy	Accuracy (%)
Cora	A	**84.95**
Cora	B	83.02
Citeseer	A	50.14
Citeseer	B	**60.25**
Chameleon	A	**43.80**
Chameleon	B	38.29

strategies: Strategy A includes both local and global memory in the prompt; Strategy B includes global memory only when fewer than two local examples are available. As shown in Table 3, Strategy A consistently performs better on structurally dense graphs like Cora and Chameleon, where high-quality local memory is readily available. In contrast, on the sparser Citeseer graph, Strategy B outperforms Strategy A by selectively avoiding potentially noisy global memory when local context is sufficient. The performance gap across datasets can be attributed to differences in structural density and label locality. Cora and Chameleon have stronger local homophily, making global memory broadly useful, while Citeseer benefits more from selective use due to sparser connections and noisier neighborhoods. As for **RQ4**, Table 4 reveals that exposing label semantics consistently harms accuracy, as LLMs tend to overfit to general label names like "machine learning" and make biased guesses.

Table 4: **Effect of Label Semantics on Accuracy.** Showing label names (e.g., "Rule Learning") in the prompt harms performance, as LLMs tend to overfit to label wording rather than reasoning from memory. We anonymize all labels (e.g., "Label_2") in our final design.

Dataset	Label Names Visible	Accuracy (%)
Cora	Yes	76.83
Cora	No (Label_ID only)	**84.95**
Citeseer	Yes	42.11
Citeseer	No (Label_ID only)	**60.25**

4 Related Works

4.1 Graph Neural Networks and Message Passing

Graph Neural Networks (GNNs) such as GCN [7], GraphSAGE [5], and GAT [22] have become the dominant paradigm in graph machine learning. These models rely on fixed, layer-wise message passing schemes that aggregate information from each node's neighbors using predefined update functions. While effective, this rigid design limits expressiveness and can cause issues like over-smoothing and over-squashing. To overcome these limitations, several works have proposed more flexible message passing strategies. CoGNN [3] introduces cooperative agents that decide whether to broadcast or listen during each round, enabling more adaptive communication. However, these agents still rely on hand-crafted utility functions and rule-based execution. In contrast, our method allows

each node to independently plan and execute its own message passing actions using an LLM-based agentic mechanism, and extends the communication space to include global semantic neighbors, not just local structural ones.

4.2 Large Language Models for Graph Tasks

Recent work has explored the use of LLMs for graph learning [19, 27]. PromptGFM [31] converts nodes into text-based prompts and uses LLMs to learn a graph vocabulary for classification. In-context RAG [10] frames node classification as a retrieval-augmented generation task, where textual neighbors are fetched and provided to the LLM for reasoning. These methods effectively leverage LLM capabilities but do not enable node-level autonomy or action planning. By contrast, we use LLMs not as passive inference engines but as active planners—the cognitive core of each agent node. The LLM decides what action to take next, what context to gather, and when to predict.

4.3 Agent-Based Graph Learning

Several prior studies have introduced the notion of "agents" in graphs, but differ from our formulation. AgentNet [14] trains neural agents to walk the graph and distinguish structures via learned exploration policies, but these agents are part of a supervised model and do not make autonomous decisions. GraphAgent [26] and GAgN [12] also propose node-agent architectures for adversarial defense and resilience, but use hardcoded 1-hop views or restricted inference logic rather than learned behaviors. AgentGNN [13] applies the agent-based paradigm to spatiotemporal graphs, modeling each node as a temporal processor. While similar in spirit, their approach is limited to sequential data and does not support open-ended, action-driven interaction or reasoning. Our formulation is fundamentally different: we treat each node as a full-fledged intelligent agent, with the ability to observe, reason, and act using LLM-powered prompts, without predefined roles, hardcoded transitions, or limited interaction space.

5 Conclusion

We introduced ReaGAN, a novel framework that treats each node in a graph as an autonomous agent capable of planning, acting, and reasoning through interactions with a frozen LLM. Unlike traditional GNNs that apply fixed, synchronous message passing rules to all nodes, ReaGAN enables self-decision at the node level—empowering each node to determine what information to gather, how to interact with others, and when to make predictions based on its own memory and context. Through this agentic formulation, ReaGAN seamlessly integrates both local structural signals and global semantic information via a unified prompting interface. Each node operates independently, combining Local Aggregation, global retrieval, and memory-guided few-shot reasoning to support fully individualized behavior. Importantly, ReaGAN achieves competitive performance using only a frozen LLM, without any gradient-based training or model fine-tuning. This highlights the promise of structured prompting and autonomous planning as a plug-and-play alternative to traditional GNNs. By shifting from rigid, fixed-rule aggregation to retrieval-augmented, node-specific decision making, ReaGAN opens a new direction for graph learning with LLM-powered agents.

6 Limitations and Future Work

ReaGAN opens a new perspective for graph learning by treating each node as a standalone agent with perception, planning, and action capabilities. While our current focus is on node classification over static text-attributed graphs and results are promising, this line of research also need to extend more experiments, like using more models and testing more graph tasks [30]. Furthermore, this agentic formulation naturally extends to broader scenarios.

In future work, we envision ReaGAN as a foundational layer in multi-agent systems [11], where each node-agent can participate in decentralized decision-making[6] or inter-agent communication. For instance, its ability to reason locally and retrieve information globally makes it a strong fit for modular systems [4] or routing-based architectures [15], where nodes may act as autonomous modules coordinating across a shared substrate. Additionally, to scale ReaGAN under constrained resources, we propose integrating it with agent orchestration frameworks such as AIOS [16]—enabling parallelized, resource-aware scheduling of reasoning agents across large graphs. Rather than being limited to graph classification, we see ReaGAN as a general blueprint for scalable agentic inference—well suited for future systems that demand fine-grained, context-aware, and communication-capable reasoning units.

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Contents

A Technical Appendices and Supplementary Material

A.1 Prompt Example

A.1.1 Planning Prompt Example

You are a node in a text-attributed graph. Your goal is to plan the next action(s) for yourself based on your current context, including memory, text features, and neighbors.

You may choose one of the following actions:

- `local aggregate`: aggregate structure neighbors' text features and store the labeled nodes in memory.

- `global aggregate`: retrieve semantically similar nodes from the whole graph and aggregate the text.

- `local+global aggregate`: perform both local and global aggregation in this step.

- `no_op`: do nothing and move to the next layer.

Node State:
- `Text Feature`: "Adverse interaction with tree depth restriction."
- `Last Local Aggregated Text Feature`: "Adverse with tree depth restriction in genetic programming."
- `Last Global Aggregated Text Feature`: "Genetic machine learning algorithms in scheduling performance problem."
- `Memory`: Contains 4 labeled examples.

Labeled Examples in Memory:

Local:

- `Label 1`: "Genetic algorithms for various scheduling problems."

Global:

- `Label 1`: "Team dynamics and performance enhancement strategies."
- `Label 2`: "Diverse machine learning techniques approach."
- `Label 6`: "Efficient learning of rectangle unions."

Planning Your Steps:

- Think like a planner: Your goal is to gather enough information for the final label prediction

- If you cannot predict the label yet(need more context to do prediction), please choose local aggregate or global aggregate.

- If local memory is not enough, do local aggregation; meanwhile, if global memory is not enough, do global aggregation. Their amount is better to be in balance.

- Otherwise, choose "no_op".

Respond strictly in JSON:

```
[
  {"action_type": "local aggregate", "global aggregate" or "no_op"},
  {"action_type": "local aggregate", "global aggregate" or "no_op"}
]
```

A.1.2 Prediction Prompt Example

You are a label prediction agent.

You will be given a new node's aggregated text feature along with a memory of labeled examples. Use the memory to infer the most likely label for this node. Respond strictly in the required JSON format.

Node State: - `Text Feature`: "Adverse interaction with tree depth restriction."
- `Local Aggregated Text Feature`: "Adverse with tree depth restriction in genetic programming."
- `Global Aggregated Text Feature`: "Genetic machine learning algorithms in scheduling performance problem."

Labeled Examples in Memory:

Local:

- `Label 1`: "Genetic algorithms for various scheduling problems."

Global:

- `Label 1`: "Team dynamics and performance enhancement strategies."
- `Label 2`: "Diverse machine learning techniques approach."
- `Label 6`: "Efficient learning of rectangle unions."

Your task is to choose the most appropriate label from the following candidates:

`["Label 0", "Label 1", "Label 2", "Label 3", "Label 4", "Label 5", "Label 6"]`

Please follow these steps in your analysis:
1. Analyze the Current Node Text: - Identify primary topics and application domain - Determine the specific problem being solved - Note core methodologies and algorithms"
2. Analyze Memory Examples: - Understand application domains for each label - Identify types of problems addressed - Note underlying methodologies
3. Compare and Weigh Evidence: - Prioritize domain and problem alignment - Evaluate methodological congruence - Consider both domain-specific techniques and general paradigms - Ensure holistic coherence in your decision
4. Avoid over-reliance on isolated keywords

Please think step by step:
First analyze memory examples and their labels, then compare them to the input text. Identify the most semantically similar memory items and explain why. Finally, decide which label best matches and explain your reasoning.

Respond strictly in JSON:

`{"action_type": "predict", "predicted_label": "Label ID"}`

A.2 Dataset Construction and Processing

We evaluate ReaGAN on three benchmark datasets: Cora, Citeseer, and Chameleon. Cora and Citeseer are standard citation networks, where nodes represent scientific papers and edges indicate citation links. Node labels correspond to research topics. Chameleon is a Wikipedia-based graph with topic-labeled web pages as nodes and hyperlink edges. Other information of these datasets are shown in Table 5

For each node, we extract a natural language text input. In Cora and Citeseer, this is obtained by concatenating the paper's title and abstract. In Chameleon, we use the full raw text provided in the dataset. To reduce prompt length and maintain LLM efficiency, we optionally apply a frozen LLM to compress these texts before use.

All node texts are stored in plain natural language format and are used in both planning and prediction prompts.

Table 5: Dataset statistics for node classification benchmarks.

Dataset	# Nodes	# Edges	# Classes
Cora	2,708	5,429	7
Citeseer	3,327	4,732	6
Chameleon	2,277	36,101	5

A.3   Hyperparameter Settings

ReaGAN.

- LLM: Qwen2.5-14B-Instruct (frozen; served via vLLM backend)
- Prompt length: 512 tokens
- RAG Top-K: 5
- Max reasoning layers: 3
- Few-shot examples per node: up to 5 from local neighbors and 5 from global retrieval
- Label prediction is enforced after the final layer